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Estrategias de precios e incertidumbre económica: Un caso de estudio aplicado al sector farmacéutico argentino usando aprendizaje automatizado

Price strategies and economic uncertainty: case-study for the Argentinian pharmaceutical sector using machine learning

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RESUMEN

Introducción: En agosto de 2019, un resultado inesperado en las elecciones presidenciales generó una variación en el tipo de cambio y la inflación esperados. El

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objetivo de este estudio es analizar la relación entre la participación de mercado y la decisión de incrementar los precios en la industria farmacéutica en Argentina.

Métodos: Se obtuvieron datos semanales en línea sobre las variaciones de los precios de algunos medicamentos mediante técnicas de *web scrapping*, y luego se aplicaron algoritmos de clasificación (*Random Forests*, *Gradient Boosting Machine* y regresión logística).

Resultados: Los resultados fueron dispares. Se encontró que la participación de mercado es importante de acuerdo a los métodos basados en árboles (*Random Forests* y *Gradient Boosting Machine*). Sin embargo, en la regresión logística, dicha variable no era significativa.

Conclusiones: La volatilidad en el tipo de cambio que siguió al resultado de la elección causó varios cambios en los precios esperados, y la estructura del mercado farmacéutico influyó sobre las reacciones de precios resultantes. Los laboratorios que tenían una mayor participación de mercado incrementaron sus precios primero.

PALABRAS CLAVE
Mercado farmacéutico; incertidumbre; aprendizaje automatizado.

ABSTRACT

Introduction: In August 2019 an unexpected presidential election result caused a change in expected exchange and inflation rates. The objective of this study is to analyze the relation between market share and the decision of increasing prices in the pharmaceutical industry in Argentina.

Methods: Online weekly data on variations of some medicine's prices were obtained using web scraping, and then classification algorithms (Random Forests, Gradient Boosting Machine and logistic regression) were applied.

Results: The results were mixed: market share was found to have high importance in tree-based methods. (Random Forests and Gradient Boosting Machine). However, in logistic regression, this variable wasn't significant.

Conclusions: Exchange rate volatility after the election result caused several changes on price expectations, and pharmaceutical market structure influenced the resulting price reactions. Laboratories which owned a higher market share rose their prices first.

KEYWORDS

Pharmaceutical market; uncertainty; machine learning.

JEL classification: C89, I10.

MSC2010: 62P20, 91B26.

1. INTRODUCTION

The relationship between market share and drug prices has been well-documented in prior literature (Lu and Comanor, 1998). Companies wielding greater market power possess the capability to set higher prices, both during the initial launch of a new drug and in the ensuing years. In high inflationary environments, companies may find it necessary to raise prices in order to sustain profits against the backdrop of escalating costs. Considering the variability in market shares among companies, and thus their differing levels of market power, it becomes a subject of inquiry whether all companies can uniformly adjust prices, or if those with greater market power can sustain or augment their profits.

In this paper we examine the relation between market share and the ability of increasing prices after an exogenous macroeconomic disruption caused by an unpredicted outcome in the presidential election which took place on August 11th, 2019. After the election, the exchange rate changed dramatically, and the Argentinian Peso (ARS) lost 25% of its value in four days. Also, the expected exchange rate for the end of the year increased significantly from 50 to 66,70 ARS (Central Bank of Argentine Republic [BCRA for its acronym in Spanish], 2019). It is worth noting that there is evidence of increase in inflation rate after devaluation in Argentina (Barberis, 2021; Castiglione, 2017; Otero et al., 2005).

These changes in currency prices and expectations might trigger price strategies among economic agents. In this regard, the pharmaceutical sector represents a significant case, as the costs of medicines could pose a barrier to the realization of the right to health, which is a key objective of public policy (Gutman and Larvarello, 2011; Perehudoff et al., 2019). This study aims to determine the influence of exchange rate increase and pharmaceutical sector concentration on prices after the election result on August 11th 2019. The rest of the paper is organized as follows. The second section presents previous theoretical and empirical studies about the relation between uncertainty, exchange rate changes and industrial concentration, and price adjustments. The third section describes methodology and data. The fourth section shows the results of this investigation. The fifth section presents a discussion of the results. Finally, the sixth section contains concluding comments.

2. BACKGROUND

Economic policy as a source of uncertainty is currently a relevant topic. This is supported by the rapid growth in literature studying the relation between uncertainty of economic policy and the behavior of several microeconomic and macroeconomic variables (Al-Thaqeb and Algharabali, 2019). A large number of existing studies have examined how Economic Policy Uncertainty Index (EPU) (Baker et al., 2016) interrelate with commodity prices (Wang et al., 2015), or consumer price index (Jones and Olson, 2013; Balcilar et al., 2016a). This approach would be appropriate in order to achieve this paper objective. However, no EPU is available in Argentina. Previous empirical research highlights that EPU and exchange rate volatility are positively correlated (Krol, 2014; Balcilar et al., 2016b; Dai et al, 2017; Olanipekun et. al, 2019; Chen et. al, 2020). Similarly, but using more frequent data, Bartshch (2019) finds the same positive correlation. Also, Kurusawa (2016) finds similar evidence, but points out that, in the long term, this correlation is able to change its sign.

The influence of the market structure on prices has been recognized by several authors. According to Herguera (1994), the relevance of market structure began to rise in the first half of the 80s. In this period, the American dollar was gaining value but the current account and import prices were unaffected. This situation motivated Mann's (1986) and Dornbusch's (1987) investigations, which represented seminal contributions that inspired a large number of studies. These studies developed partial equilibrium models in order to explain why prices in different sectors (even different firms) changed in different magnitudes as a response to exchange rate variations. To this end, Kirman and Phlips (1996) developed a model that shows the relevance of market share to the impact of exchange rate variations on consumer prices.

Several empirical investigations also suggest that price variation, as a response to exchange rate changes, is different between sectors (Bhattacharya et. al, 2008; Mallick and Marques, 2010; He et. al, 2015; Thorbecke and Kato, 2018). However, only some of them point out the market characteristics as the cause of these differences (Bhattacharya et. al, 2008; Mallick and Marques, 2010; He et. al, 2015; Thorbecke and Kato, 2018).

2.1. Pharmaceutical sector in Argentina

The pharmaceutical sector in Argentina can be classified as an imperfectly competitive market, characterized by production and consumption complexities. First, the demand is inelastic due to difficulties of avoiding medicine purchasing when needed to reestablish or maintain a healthy status. Second, on the supply side, marketing strategies are implemented by firms, affecting the consumer power of decision, and providing minimum information about their products (Bramuglia et. al., 2015). Third, even though all laboratories represent a low market share (Urbitzondo et al., 2013), the two most important pharmaceutical business chambers own 79% of consumer sales.

Similarly, a high concentration is able to be found if the market is divided by therapeutic class (3rd level classification of ATC). In 2019, 4.5% of these divided markets were monopolies, while nearly a 25% of them were characterized by a Herfindahl-Hirschman Index (HHI) higher than 7500 (Statement Nº 113 National Commission of Competition Defense [CNDC for its acronym in Spanish], 2019). Even though a part of the supply is offered by the public sector, most of governmental laboratories are not authorized by the National Administration of Medicines, Food and Medical Technology (ANMAT for its acronym in Spanish) to sell their products to the public (Santos and Thomas, 2018; Bramuglia et al., 2012). Also, these laboratories are located in Buenos Aires, Santa Fé and Córdoba, which represents a non-uniform territorial distribution (Santos and Thomas, 2018).

This sector interdependence is another relevant factor, mainly, due to its relation to the health care market. This market's distortions are able to impact on the pharmaceutical one (Alomar et al., 2005). Similarly, medicines are an important component of many households' expenditures which can represent a regressive income factor (Apella, 2006; Perticara, 2008).

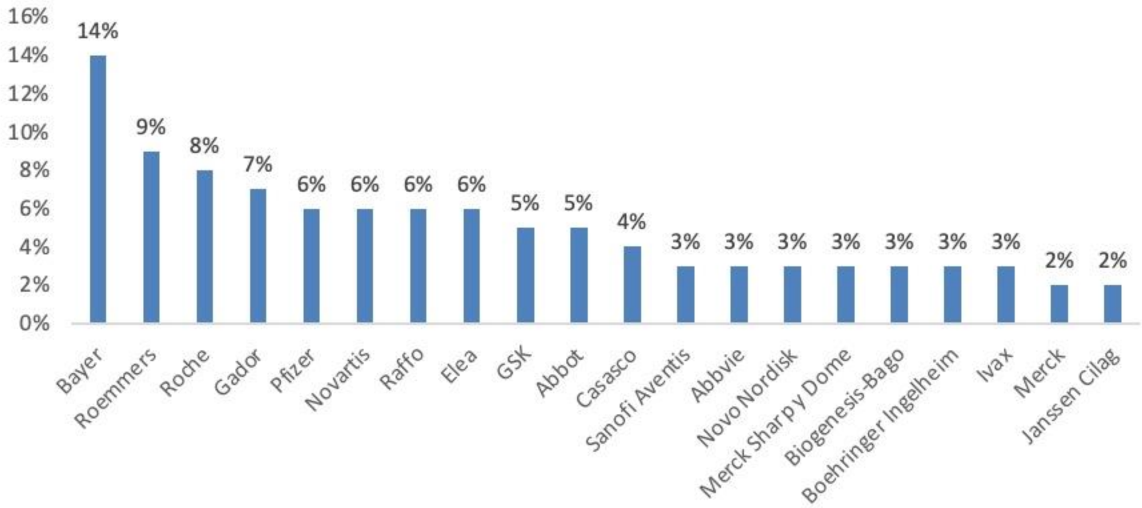
3. DATA AND METHODS

We obtained medicine prices by web scraping, which is an automatized computational technique used to extract high frequency online information at a lower cost than traditional price surveys. This procedure was applied to the web catalog of a retail pharmacy chain called Farmacity and a total of 29,034 observations were retrieved, one of each week between 12th August and 3rd September. 46% of these observations were classified as price increases, which represents a balanced sample.

On the other hand, market participation data, understood as the producing laboratory's share of retail sales, were obtained from a technical report done by the CNDC. These data are presented in Graph 1.

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

Graph 1. Retail sales share by laboratory



Source: Own elaboration based on a technical report of pharmaceutical market structure (Statement N° 113 CNDC, 2019).

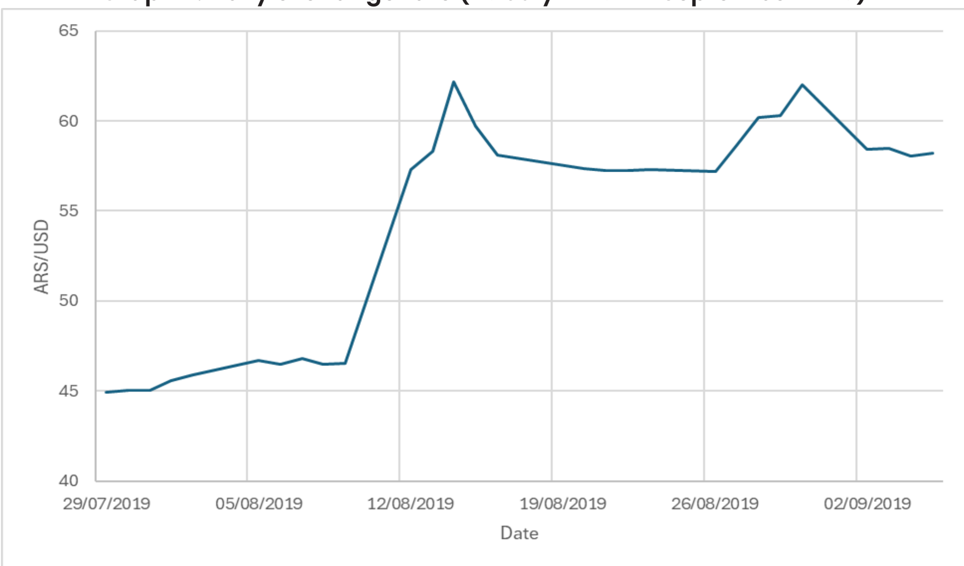
A dependent variable (aum_t) was defined as a dummy equal to one if a medicine price, measured in ARS, was higher than the previous week. Otherwise, aum_t was set to zero. As independent variables we used the market share of the medicine manufacturing laboratory ($conc$) and the difference between the exchange rate in the previous week and the one before (v_usd). The variable v_usd represents the observed exchange rate variation.

The variable that represents the exchange rate's evolution is established as the difference of the maximum values (p_usd) of the two previous weeks, as exposed in the following equation

$$vousdmx_t = \{p\_usd_{t-1}\} - \{p\_usd_{t-2}\}$$

The exchange rate was obtained from the sale price of the American Dollar, as published by BCRA. Graph 2 depicts the daily exchange rates during the period of analysis. A sudden increase is observed after August 11, 2019, the day of the presidential election.

Graph 2. Daily exchange rate (29 July 2019 - 5 September 2019)



Source: BCRA (2024).

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

We find it important to distinguish between pharmaceutical national laboratories and foreign counterparts. A dichotomous variable (lab_arg) takes a value of 1 if the laboratory producing the medicine is Argentine, and 0 if it is a foreign laboratory. This information was extracted from the Industrial Chamber of Argentine Pharmaceutical Laboratories webpage (CILFA, acronym in Spanish).

The choice of whether to increase the price or not may be significantly influenced by the drug associated with each medicine. For this reason, we introduce principal drugs as dichotomous variables. We consider only the 15 most frequently used drugs in our sample.

Additionally, the weeks following the election results serve as an important signal for understanding how the price increase adjusts over time. It is expected that detecting a price increase becomes less likely in the subsequent weeks after the event. Therefore, an ordinal variable (t) is included in the estimations.

To fulfill the objectives of this investigation, we conducted estimations using logistic regression, Random Forests, and Gradient Boosting Machine. The dataset was split into a training set (90%) and a test set (10%). Therefore, the training set was utilized for parameterizing the models, and the performance of each model was evaluated using the test set. All estimations were implemented using the R programming language (R Core Team, 2022). With the exception of logistic regression, specific packages in R were employed to execute the algorithms.

The Logistic Regression is useful when the dependent variable is binary. A Bernoulli distribution of the predicted event is assumed, what in this paper is the increase of a medicine price ($aum = 1$). The regression's parameters correspond to the independent variables and the regression is modeled as follows

$$P\left(x_i\right) = \frac{expexp\left(\alpha + \beta x_i\right)}{1 + exp\left(\alpha + \beta x_i\right)}$$

where x is the independent variable vector. If the denominator is simplified and the exponents are deleted, the previous equation is expressed as follows

$$ln\left(\frac{P(x_i)}{1 - P\left(x_i\right)}\right) = \alpha + \beta x_i$$

The previous expression indicates that the logistic model can be stated as the quotient of event probabilities (odds-ratio). Also, it shows how the coefficients directly impact on this ratio (Hair et al., 2014).

Breiman (2001) has suggested the utilization of classification and regression trees (CART) in order to generate a classifier algorithm by applying the mean of a large enough number of interrelated trees. This algorithm, called Random Forest (RF), assumes that multiple tree creation reduces the variability in comparison to any individual tree, and minimizes the final model overfitting. This corresponds to an assembly methodology, because the final model is composed of hundreds (or thousands) of predictive ones, independently created (Hastie, 2009).

The first step consists of subsampling a part of the observations by bootstrapping (Typically, 2/3 of the training data). Every generated tree will be composed by a number of $z < x$ predictors (James et al., 2013). This procedure is performed n times, generating a different classification tree every time.

As a result, the prediction of a higher price is decided by votes, which means that the medicine final classification will depend on how it was classified most of the times:

$$\hat{C}_x^n(x) = majority\ votes\ \{\hat{C}\}_1^n$$

In this research, the implementation of RF algorithm is through the packages caret (Kuhn, 2008) and Ranger (Liaw & Wiener, 2002) from R.

In contrast to RF, in which every tree is independent to the previous ones, Friedman (2001) has suggested the construction of an algorithm by a sequential tree building, which allows using previous tree's information. This methodology is named Gradient Boosting Machine (GBM), and it minimizes a loss function (h) that measures the difference between the real and estimated value.

Consequently, the classifying method proceeds recursively n times in order to adjust the h parameter using previous models (F). Therefore, the last iteration of the model is able to be established as

$$F_n^d = F_{n-1}^d + \beta\, h(x)$$

The β value is called the learning rate and, in comparison to RF, the algorithm is indifferent about the variables employed in every tree, but it considers the ramifications in each one (d). The implementation of GBM applied was with the gbm package (Greenwell et al.,2022)

An inherent challenge in tree-based models such as Gradient Boosting Machine (GBM) and Random Forests (RF) is the loss of interpretability. Unlike linear models like logistic regression, where coefficients indicate the contribution of each variable to the outcome, "black-box" models like RF and GBM lack this transparency.

Addressing this issue, an intriguing question arises: how can we evaluate the impact of features in such "black-box" models? A valuable approach to enhance interpretability in machine learning is the utilization of model-agnostic methods. The model-agnostic approach refrains from imposing assumptions about the intrinsic characteristics of the model (Molnar, 2022).

While various methods exist, we specifically selected the permutation feature importance method to assess the interpretability of our tree-based models. This approach enhances explicability without relying on assumptions about the internal structure of the model.

In the feature importance procedure, the conventional approach involves running a model with all variables in the original data (X). Subsequently, the variable of interest (x_j) in the vector with the total independent variables (X) is permuted, and the model is rerun. The resulting matrix X_{perm} disrupts the linkage between $x_j$and the variable of interest in predicting aum. The metric used to measure the loss of feature importance due to permutation is the cross entropy (CE), which quantifies incorrect predictions. This metric is defined as:

$$CE(aum, \widehat{aum}) = \frac{1}{n}\sum_{i=1}^{n}[\, aum_{t,i} \log\log\ (p_i) + \left(1 - aum_{t,i}\right) \log\log\ (1 - p_i)]$$

Here n is the probability that a price was higher than the previous week, and a low value of CE indicates a well-fit model. High values of CE suggest that the variable is crucial to the prediction, as its absence adversely affects the model's performance. In contrast, the package iml (Molnar et al., 2018) provides an interesting application of Feature Permutation Importance.

4. RESULTS

The logistic regression estimation results, as presented in Table 1, indicate a significant relationship between a price increase and variations in the exchange rate. Additionally, it reveals a statistically significant association between the decision to raise prices and whether the producer is a national laboratory.

The week following the elections plays a crucial role in the strategic decision to anticipate and adjust the current prices. As expected, a greater number of weeks after the elections negatively and significantly impacts the likelihood of a price increase.

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

Table 1. Logistic regression

	Coefficient	Standard error	t-value	p-value
(Intercept)	-0,676	0,055	-12,288	0,000*
t	-0,145	0,022	-6,704	0,000*
conc	-0,946	0,732	-1,292	0,196
v_usd	7,444	0,121	61,548	0,000*
lab_arg	0,313	0,036	8,633	0,000*
carvedilol	-0,065	0,130	-0,500	0,617
metformina	-0,035	0,132	-0,267	0,789
pregabalina	0,252	0,136	1,847	0,065
rosuvastatina	0,203	0,142	1,434	0,152
quetiapina	0,232	0,157	1,476	0,140
alprazolam	0,170	0,154	1,107	0,268
enalapril	0,533	0,153	3,480	0,001*
ibuprofeno	0,461	0,155	2,984	0,003*
diclofenac	-0,225	0,158	-1,422	0,155
amoxicilina	0,133	0,159	0,836	0,403
atorvastatín	0,518	0,162	3,190	0,001*
sildenafil	-0,085	0,164	-0,521	0,603
clonazepam	0,236	0,167	1,416	0,157
risperidona	-0,152	0,177	-0,859	0,390
claritromicina	0,026	0,175	0,146	0,884

N = 28807 AIC = 27872 *'=: significant (Confidence Interval of 95%)

Source: own elaboration.

Another noteworthy finding is the lack of significance regarding the market share. According to the logistic regression estimation, there seems to be no linear relationship between the decision to increase the selling price and the percentage of sales held by the laboratory across the brand.

The confusion matrix of the logistic regression (Table 2) illustrates the model's performance on the training set. The logistic regression accuracy stands at 59.94%, with better performance in predicting non-increased prices (60.36%) than in predicting price increases (56.52%).

Table 2. Confusion matrix (reg. log.)

		Observed		
		Not increased	**Increased**	**% correc. clasif.**
Predicted	**Not increased**	1701	1134	60,00%
	Increased	20	26	56.52%
			Accuracy	59.94%

Source: own elaboration.

When applying the Random Forest (RF) model, the prediction results are presented in Table 3. We utilized a grid search with cross-validation (CV=5) to fine-tune the model, adjusting the following hyperparameters: the number of trees, features in each tree, and the minimum node size.

For the number of trees, the optimal choice was 1000, selected from a range of 500 to 3000 trees. Regarding the features, we experimented with values between 5 and 19, and the highest performance was achieved with the maximum number of features (19). The chosen node size was 5, with values explored in the range of 1 to 5.

The accuracy of the RF model stands at 73.81%, significantly surpassing that of logistic regression. Furthermore, the correct prediction of a price increase is 84.40%, outperforming predictions of non-increases (74.17%).

Table 3. Confusion matrix (RF.)

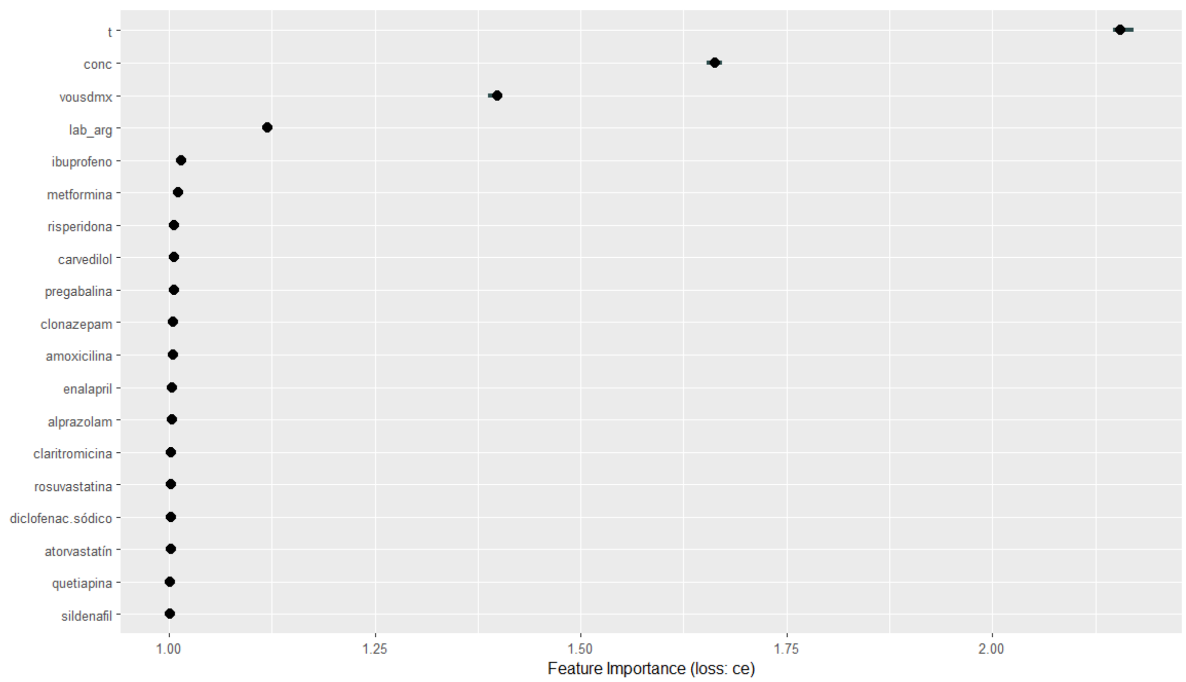
		Observed		
		Not increased	**Increased**	**% correc. clasif.**
Predicted	**Not increased**	1528	532	74.17%
	Increased	193	628	84.40%
			Accuracy	74.85%

Source: own elaboration.

An essential consideration is the interpretability of the Random Forest (RF) model. Graph 3 illustrates the feature importance based on cross-entropy. According to the RF analysis, the most relevant features are the week (t) of the election, market share (conc), and the difference between the exchange rates in the week (vousdmx).

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

Graph 3. Feature Importance (RF)



Source: own elaboration.

Similar to the RF, the Gradient Boosting Machine (GBM) was fine-tuned using a grid search with cross-validation (CV=5). In this model, we adjusted the number of trees, learning rate, and the number of splits it performs on a tree.

The optimal performance of this model was achieved with 1500 trees, tested in a range from 500 to 3000 trees. The most effective learning rate was found to be 0.0091, explored with steps of 0.0001, and 20 splits on a tree, tested within a range of 5 to 40 splits.

Table 4. Confusion matrix (GBM)

		Observed		
		Not increased	**Increased**	**% correc. clasif.**
Predicted	**Not increased**	1528	531	74,21%
	Increased	193	629	76,52
			Accuracy	74,87%

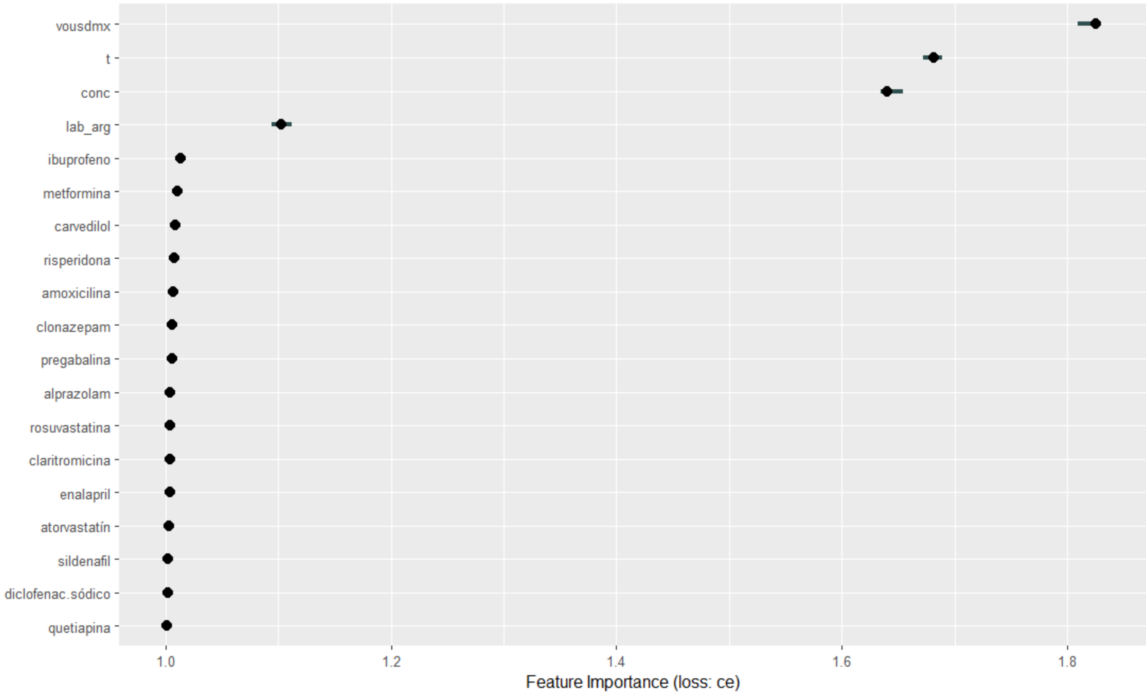
Source: own elaboration.

Table 4 presents the confusion matrix, indicating that the accuracy of this model is 74.87%, which is comparable to RF. However, the key distinction lies in the analysis of feature importance. Graph

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

4 illustrates that the most critical feature is the variation in the exchange rate, followed by the week (t), and in the third position, the market share (conc). Additionally, the nationality of the laboratory (whether Argentine or not) plays a significant role in the decision to increase the price.

Graph 4. Feature Importance (GBM)

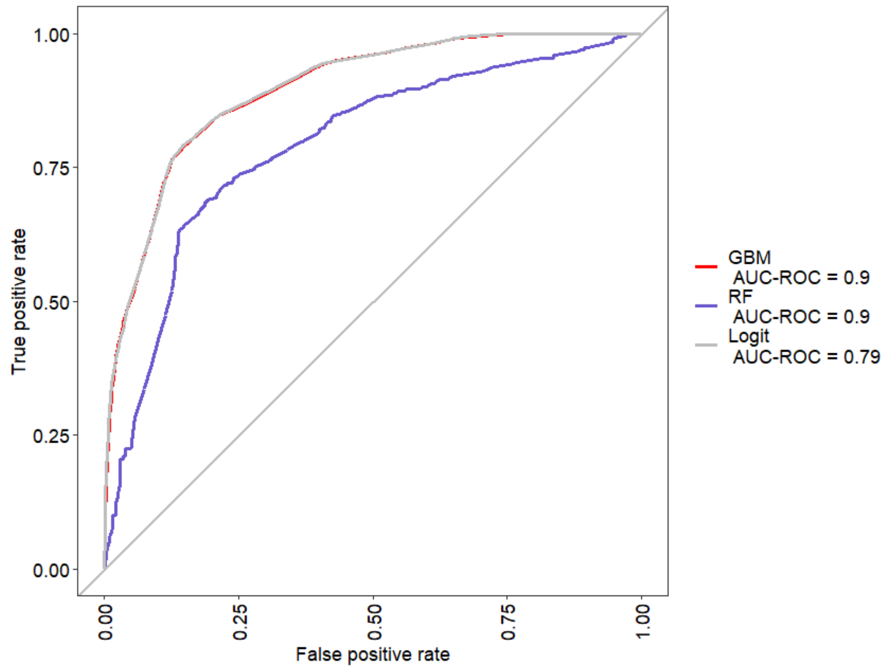


Source: own elaboration.

An important insight provided by both Random Forest (RF) and Gradient Boosting Machine (GBM) is the significance of the market share as a crucial variable in prediction. The absence of significance for this variable in logistic regression suggests that it exhibits a nonlinear relationship with the logarithm of the odd ratio of the decision to increase the price. Additionally, variables such as exchange rate (vousdmx), week of the change (t), and the Argentinean origin of the laboratory (lab_arg) consistently appear as the most important features in both models for achieving accurate predictions.

N. 38, 2024 - ISSN: 1886-516X - DOI: 10.46661/revmetodoscuanteconempresa.6407 - [Págs. 1-16]

Graph 5. ROC curves.



Source: own elaboration.

The analysis of the Receiver Operating Characteristics (ROC) curves and the area under them indicates that logistic regression performs less effectively compared to other methods, as illustrated in Graph 5. According to this analysis, the superior predictive power is evident in GBM and RF, showcasing the lowest false positive rates and highest true positive rates across all possible cutoff criteria.

5. DISCUSSION

Our investigation enhances this literature by empiric estimations using Argentinian data. These estimations support the hypothesis that the response of pharmaceutical consumer prices to exchange rate variations is influenced by the market structure. However, this paper focuses on the decision of changing prices instead of the magnitude of these changes. Probably, in order to complete the investigation, further estimations will analyze the cost of the menu phenomenon using these data.

Analyzing the results of logistic regression, the association between the most prevalent drugs shows significance for ibuprofen, atorvastatin, and enalapril. Regarding ibuprofen, it is essential to emphasize its analgesic effect and its categorization as an Over-the-Counter (OTC) medicine, strongly linked with self-medication (Aguilar et al., 2015).

Conversely, atorvastatin is employed for reducing cholesterol levels in individuals diagnosed with high blood cholesterol and for the prevention of heart disease (Mayo Clinic, 2023). Enalapril, on the other hand, is used for managing elevated blood pressure and is employed in combination with other medications for the treatment of congestive heart failure (Medications

Committee of the Spanish Association of Pediatrics, 2015).

It is worth noting that national laboratories are associated with a higher likelihood of price increase. This result might be explained by different factors. Firstly, this group could have an important knowledge about the uncertainty in macroeconomic changes for the Argentina situation. Secondly, these companies could be an important set of laboratories who constitute a pressure group taking the decisions in the same way with a high market share. This last potential explanation is reinforced for the absence of significance of the variable conc in the logistic regression. All these possible causes are a matter of further research.

6. CONCLUSIONS

In the aftermath of the election results on August 11th 2019, the pharmaceutical sector witnessed several changes in price expectations due to exchange rate volatility. This study explored the phenomenon, considering market shares of manufacturing laboratories, variations in the current exchange rate, the specific drug of the medicine, and whether the producer is an Argentinean laboratory as relevant explanatory variables.

The logistic regression estimation revealed that national laboratories were the first to increase their prices. These findings support the notion that such laboratories may possess more information about the national economic situation. Conversely, market share did not prove to be significant. The variation in the exchange rate showed the highest coefficient, indicating evidence of pass-through. Weeks after the election, specific medicines demonstrated an impact on the decision to increase prices.

Other classification techniques were applied, highlighting higher predictive power in tree-based methods (GBM and RF). A key result from these methods was the improvement in prediction accuracy and the identification of important features. Notably, market share emerged as a crucial explanatory variable. It's essential to emphasize that these models are constructed considering nonlinear relationships between variables.

Moreover, the study underscores the importance of public policy in the pharmaceutical market, given its impact on the objective of universal health coverage. This issue is of significant public interest due to its profound implications for people's well-being (Alomar et al., 2006).

Finally, for future research directions, it is crucial to analyze additional explanatory variables. Given the availability of weekly prices, investigating how dynamic price adjustments occur under a menu cost theoretical framework would provide valuable insights.

REFERENCES

Aguilar, A., Ascitelli, A., Carosella, L., Izurieta, M., Perandones, M., Soverchia, S., Yapur, C., Zolezzi, C., Barreña, A., Genaro, A. M., & Scublinsky, D. (2015). Prevalencia de automedicación de antiinflamatorios y analgésicos en la práctica ambulatoria. *Revista Argentina de Reumatología*, *26*(3), 13-15. https://revistasar.org.ar/revistas/2015/n3/2_articulo_original.pdf

Alomar, A. V., Moscoso, N. S. y Larrosa, J. M. C. (2006). *Determinantes del acceso a los medicamentos: El caso argentino.* Artículo presentado en la XLI Reunión Anual de la Asociación Argentina de Economía Política, Salta, Argentina. https://bd.aaep.org.ar/anales/works/works2006/Alomar_Moscoso_Larrosa.pdf

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. The Journal of Economic Asymmetries, 20, e00133. https://doi.org/10.1016/j.jeca.2019.e00133

Apella, I. (2009). Gasto de bolsillo en salud e impacto financiero sobre los adultos mayores en argentina. Anales de La Asociación Argentina de Economía Política, XLIV Reunión Anual. https://aaep.org.ar/anales/works/works2009/apella.pdf

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics, 131 (4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Balcilar, M., Gupta, R. and Jooste, C. (2016a). Long memory, economic policy uncertainty and forecasting US inflation: A Bayesian VARFIMA approach. Applied Economics, 49 (11), 1047-1054. https://doi.org/10.1080/00036846.2016.1210777

Balcilar, M., Gupta, R., Kyei, C. and Wohar, M. E. (2016b). Does economic policy uncertainty predict exchange rate returns and volatility? Evidence from a nonparametric causality-in-quantiles test. Open Economies Review, 27, 229-250. https://doi.org/10.1007/s11079-016-9388-x

Barberis, M. (2021). Asimetrías del traspaso del tipo de cambio a precios: el caso argentino 2004-2019. Ensayos Económicos (76), 103–143.

Bartsch, Z. (2019). Economic policy uncertainty and dollar-pound exchange rate return volatility. Journal of International Money and Finance, 98, 102067. https://doi.org/10.1016/j.jimonfin.2019.102067

Bhattacharya, P. S., Karayalcin, C. A., & Thomakos, D. D. (2008). Exchange rate pass-through and relative prices: An industry-level empirical investigation. Journal of International Money and Finance, 27, 1135-1160. https://doi.org/10.1016/j.jimonfin.2008.05.004

Bramuglia, C., Abrutzky, R., y Godio, C. (2012). *Análisis de la industria farmacéutica estatal en Argentina* (Documento de Jóvenes Investigadores nº 34). Instituto de Investigaciones Gino Germani, Facultad de Ciencias Sociales, Universidad de Buenos Aires. https://biblioteca.clacso.edu.ar/Argentina/iigg-uba/20120801053021/dji34.pdf

Bramuglia, C., Abrutzky, R., & Godio, C. (2015). El perfil de la industria farmacéutica de la Argentina. Interrogantes a mediano plazo. *Ciencia, docencia y tecnología*, *26* (51), 102-130. https://pcient.uner.edu.ar/index.php/cdyt/article/view/55

Breiman, L. (2001). Random Forests. Machine Learning, 45 (1), 5-32. https://doi.org/10.1023/A:1010933404324

Castiglione, B. (2017). El traspaso a precios de las depreciaciones cambiarias: Una estimación VECM para el caso argentino. Premio Anual de Investigación Económica Dr. Raúl Prebisch.

Central Bank of Argentinian Republic (2019). *Resultados del Relevamiento de Expectativas de Mercado.* http://www.bcra.gob.ar/Pdfs/PublicacionesEstadisticas/REM200131%20Resultados%20web.pdf

Central Bank of Argentinian Republic (2024). *Principales variables.* https://www.bcra.gob.ar/PublicacionesEstadisticas/Principales_variables.asp

Chen, L., Du, Z., & Hu, Z. (2020). Impact of economic policy uncertainty on exchange rate volatility of China. Finance Research Letters, 32, 101266. https://doi.org/10.1016/j.frl.2019.08.014

Dai, Y., Zhang, J., Yu, X., & Li, X. (2017). Causality between economic policy uncertainty and exchange rate in China with considering quantile differences. Theoretical and Applied Economics, 24 (3), 29-38. http://www.ectap.ro/causality-between-economic-policy-uncertainty-and-exchangerate-in-china-with-considering-quantile-differences-yin-dai_jing-wen-zhang_xiu-zhen-yu_xin-li/a1291/

Dornbusch, R. (1987). Exchange rates and prices. The American Economic Review, 77 (1), 93-106. https://www.jstor.org/stable/1806731

Friedman, J. (2001). Greedy function approximation: A gradient boosting machine. The Annals of Statistics, 29 (5), 1189-1232. https://doi.org/10.1214/aos/1013203451

Greenwell B., Boehmke B. & Cunningham J. (2022). Gbm: Generalized Boosted Regression Models. R package version 2.1.8.1, https://CRAN.R-project.org/package=gbm

Gutman, G. & Lavarello, P. (2011). Formas de organización de las empresas biotechnológicas en el sector farmacéutico argentino. Desarrollo Económico, 51 (201), 81-105. https://www.jstor.org/stable/23612337

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate data analysis: Pearson new international edition. Essex: Pearson Education Limited.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). The elements of statistical learning: Data mining, inference, and prediction. Springer Science & Business Media.

He, B., Zhu, H., Chen, D., & Shi, Y. (2015). On pass-through of RMB exchange rate to prices of different industries. Procedia Computer Science, 55, 886-895. https://doi.org/10.1016/j.procs.2015.07.146

Herguera, I. (1994). Industry price adjustment to exchange rate fluctuations in oligopoly: An empirical study of the pass-through relationship determinants in the Spanish automobile industry, 1981-1991 (PhD Thesis). European University Institute, Florence. https://op.europa.eu/es/publication-detail/-/publication/213f69a9-c5b3-4219-bf1d-a5195f9ab738

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). New York: springer.

Jones, P. M., & Olson, E. (2013). The time-varying correlation between uncertainty, output and inflation: Evidence from a DCC-GARCH model. Economics Letters, 118, 33-37. https://doi.org/10.1016/j.econlet.2012.09.012

Kirman, A., & Phlips, L. (1996). Exchange rate pass-through and market structure. Journal of Economics, 64 (2), 129-154. https://doi.org/10.1007/BF01250111

Krol, R. (2014). Economic policy uncertainty and exchange rate volatility. International Finance, 17 (2), 241-255. https://doi.org/10.1111/infi.12049

Kurasawa, K. (2016). Policy uncertainty and foreign exchange rates: The DCC-GARCH model of the US/Japanese foreign exchange rate. International Journal of Economic Sciences, 5 (4), 1-19. https://doi.org/10.52950/ES.2016.5.4.001

Kuhn, M. (2008). Building Predictive Models in R Using the caret Package. Journal of Statistical Software, 28(5), 1–26. https://doi.org/10.18637/jss.v028.i05-

Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *The R Journal*, *2/3*, 18-22. https://journal.r-project.org/articles/RN-2002-022/RN-2002-022.pdf

Lu, Z. J., & Comanor, W. S. (1998). Strategic Pricing of New Pharmaceuticals. The Review of Economics and Statistics, 80(1), 108–118.

Mallick, S., & Marques, H. (2010). Data frequency and exchange rate pass-through: Evidence from India's exports. International Review of Economics and Finance, 19, 13-22. https://doi.org/10.1016/j.iref.2009.02.007

Mann, C. L. (1986). Prices, profit margins, and exchange rates. Federal Reserve Bulletin, (Jun), 366-379. https://fraser.stlouisfed.org/files/docs/publications/FRB/pages/1985-1989/31910_1985-1989.pdf

Mayo Clinic. (2023). Drugs and Supplements. Atorvastatin (Oral Route). https://www.mayoclinic.org/diseases-conditions/dementia/symptoms-causes/syc-20352013

Medications Committee of the Spanish Association of Pediatrics (2015). Pediamécum. Edición 2015. https://www.aeped.es/comite-medicamentos/pediamecum/enalapril.

Molnar, C. (2022). Interpretable Machine Learning: A Guide for Making Black Box Models Explainable (2nd ed.). https://christophm.github.io/interpretable-ml-book/

Molnar, C., Casalicchio, G., & Bischl, B. (2018). iml: An R package for Interpretable Machine Learning. *The Journal of Open Source Software*, *3* (26), 786. https://doi.org/10.21105/joss.00786

Olanipekun, I. O., Olasehinde-Williams, G., & Güngör, H. (2019). Impact of economic policy uncertainty on exchange market pressure. SAGE Open, 9(3), 1-13. https://doi.org/10.1177%2F2158244019876275

Otero, G. A., Cadelli, M. E., Carbajal, R., y Cerimedo, F. (2005). *Explorando los determinantes del traspaso de la devaluación a precios*: *Una explicación del éxito devaluatorio argentino de 2002* (documento de trabajo). Grupo de Investigación Económica (GIE) del Ministerio de Economía de la Provincia de Buenos Aires. https://www.ec.gba.gov.ar/prensa/Archivos/Julio2005.pdf

Perticara, M. (2008). Incidencia de los gastos de bolsillo en salud en siete países latinoamericanos. Santos, G., and Thomas, H. (2018). Producción pública de medicamentos. Ciencia, Tecnología y Política, 1(1), 007-007. https://www.cepal.org/es/publicaciones/6146-incidencia-gastos-bolsillo-salud-siete-paises-latinoamericanos

Perehudoff, S. K., Alexandrov, N. V., & Hogerzeil, H. V. (2019). The right to health as the basis for universal health coverage: A cross-national analysis of national medicines policies of 71 countries. PLOS ONE, 14(6), e0215577. https://doi.org/10.1371/journal.pone.0215577

R Core Team (2022). R: A language and environment for statistica lcomputing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Santos, G., y Thomas, H. (2018). Producción pública de medicamentos: desafíos para una política estratégica en materia de salud, *Ciencia, Tecnología y Política*, *1* (1), 1-7. https://doi.org/10.24215/26183188e007

Statement Nº 113/2019. National Commission of Competition Defense, Buenos Aires, Argentina, 23 de December 2019. https://www.argentina.gob.ar/sites/default/files/im._4_-_medicamentos_-_disposicion_y_anexo.pdf

Thorbecke, W., & Kato, A. (2018). Exchange rates and the Swiss economy. Journal of Policy Modeling, 40 (6), 1182-1199. https://doi.org/10.1016/j.jpolmod.2018.07.002

Urbiztondo, S., Cont, W., & Panadeiros, M. (2013). La competencia en el segmento upstream de la industria farmacéutica argentina. Documento de trabajo, 121. http://www.fiel.org/publicaciones/Documentos/DOC_TRAB_1396372329842.pdf

Wang, Y., Zhang, B., Diao, X., & Wu, C. (2015). Commodity price changes and the predictability of economic policy uncertainty. Economics Letters, 127, 39-42. https://doi.org/10.1016/j.econlet.2014.12.030